Circles, Posts and Privacy in Egocentric Social Networks: An Exploratory Visualization Approach

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***Abstract*—The users in Online Social Networks (OSN) may share private information with wrong friends. One approach to tackle this issue is by applying community discovery methods in egocentric networks to automatically generate friend circles for the user. There is however a discrepancy between the predicted circles and the circles that the user has in mind. A deep rooted reason is that it only makes sense when the circles are considered under certain usage. We designed and implemented an exploratory visualization tool that can help users determine the visibilities of their online posts. More specifically, we first examined the state-of-the-art community discovery methods for egocentric networks, then proposed a new visualization design with fine-grained control for the user to interact with the circles and make visibility decisions. Finally, we conducted an experimental user study evaluating the usefulness of this design.**

Keywords—Online Social Networks; Visualization; Circles; Design; Privacy

I. Introduction

An Online Social Network (OSN) today can hold hundreds of millions of users[1], such as Facebook. Large amount of online personal information is exchanged daily. This phenomenon has raised privacy concerns. Two types of such concerns can be distinguished: *social* and *instrumental* [1]. *Social privacy* concerns how and when personal information is shared with others within an OSN (e.g. [2], [3], [4]), whereas *instrumental privacy* concerns the personal data access by service providers, governments or other corporations (e.g. [5], [6]). In this paper, we focus on *social privacy*. More specifically, we are interested in the tools that help users control the flow of personal information shared with friends in Egocentric OSN (EOSN). An EOSN is a network with the vertices representing people and the edges representing certain relationships among them. It is centered on one person whom we call the ego. The friends of the ego, whom we call the alters, must be directly linked to the ego. An alter can also connect to other alters.

As previous studies have suggested [7], [8], [2], [9], in order to manage the personal information flow, it is important for the user to categorize the friends into circles, lists or communities[2]. The community discovery algorithms may help users in this regard. However, as elaborated in Section II, there is a discrepancy between the predicted circles and the circles that the user has in mind. This calls for a type of application that can help its users effectively utilize the output of a community discovery algorithm. In this paper, we introduce one such application.

The contributions of this paper are: First, an exploratory tool is described. The tool is to help its users categorize friends more effectively in EOSN. Second, we describe an experimental user study to evaluate the effectiveness of the circles when a user makes visibility decisions about posts. Third, a new kind of interactive visualization was designed to assist in fine-grained exploration of hierarchical circles.

The structure of this paper is as follows: In Section II, we motivate our design choices by reviewing related works. Section III describes the design of the tool. Section IV gives an account of our user study for evaluating the tool. In Section V, we conclude by a discussion of future work and a summary of the paper.

II. Related Works and Design Choices

A. Notation

We denote an EOSN as a graph $G = (V, E, F)$, in which V is a set of vertices, with each vertex v an alter, usually labeled with a name. E is a set of edges with each edge $e = (u, v)$, with $u, v \in V$ representing a relation between u and v. For example, a relation can be formed if u and v are mutual friends in G or u follows v. F is a set of features describing V. A typical feature can be v's profile information, such as "gender is female". There exists a function assigning features to vertices, $\phi : V \times F \to \{f, v\}$. We denote an algorithm-predicted circle as c and a manual circle created by a user as $\tilde{c}$, with $c \subseteq V$, $\tilde{c} \subseteq V$. Correspondingly, the set of generated circles is denoted as C and user-created circles as $\tilde{C}$. We use p to denote a post. A post may include updating status, changing profile information, uploading/sharing photos/videos, tagging

[1]http://en.wikipedia.org/wiki/List_of_social_networking_websites

[2]We use "circle", "list" and "community" interchangeably in this paper. These words all refer to a collection of alters in an EOSN, usually with common characteristics. However, "community" is often used as a more general term in the field of community discovery algorithms, while "circle" and "list" are mentioned more in the EOSN context.

names in photos, liking, commenting, etc. A *Visibility Decision* refers to an ego's decision on the visibility of his post to each alter.

B. Community Discovery Algorithms

Community discovery in networks is a general problem and many algorithms exist [10], [11]. There are three categories of community discovery algorithms based on the types of input data — *Category 1* takes only the network E into account. The relationship of mutual friends or follower-followee forms an edge. In general, this category produces circles composed of densely connected alters. *Category 2* only considers the features F. This category produces circles composed of alters sharing common feature(s). *Category 3* makes use of both E and F. We are interested in the algorithms that may predict similar circles as the ones a user would manually create.

McAuley and Leskovec [12] examined eight community discovery algorithms from the above three categories and proposed a new model that outperforms the others. $Accuracy(c, \tilde{c})$ (Equation 1) is used to determine how well a set of predicted circles matches its manual counterpart. BER is short for Balanced Error Rate. The linear assignment between $c \in C$ and $\tilde{c} \in \tilde{C}$ is determined by the Munkres algorithm [13]. Let H be the set of pairs of circles that are matched. The average accuracy $Accuracy(C, \tilde{C})$ between the predicted circles C and the manual circles $\tilde{C}$ is shown in Equation 2.

$$\begin{aligned} Accuracy(c, \tilde{c}) &= 1 - BER(c, \tilde{c}) \\ with\ BER(c, \tilde{c}) &= \frac{1}{2}\left(\frac{|c \backslash \tilde{c}|}{|c|} + \frac{|\tilde{c} \backslash c|}{|\tilde{c}|}\right) \end{aligned} \tag{1}$$

$$Accuracy(C, \tilde{C}) = \frac{\sum_{(c,\tilde{c}) \in H} Accuracy(c, \tilde{c})}{min(|C|, |\tilde{C}|)} \tag{2}$$

For convenience, we name the model and the corresponding algorithm in [12] as GMF, short for "Generative Model for Friendships". GMF takes profile information to construct edge probabilities based on the EOSN network. The circles are then found by maximizing the overall probability. The number of circles needs to be pre-determined. GMF can also be computationally expensive — we ran it on the ten Facebook users' data provided in [12], it took more than an hour on average to generate circles for each user[3]. These limitations make us consider alternative algorithms for our tool. Another community discovery algorithm developed by Newman [14] is not among the eight baselines in [12]. It takes only the network data as input. The circles are found by maximizing the modularity of the network[4], and the number of circles is automatically determined. With the "Jmod" implementation of Newman's algorithm [15], the average computation time for each of the ten Facebook users is less than eight seconds. For simplicity, we refer to this algorithm as MOD. Figure 1 summarizes the performances in accuracy of the two algorithms running on the ten Facebook users' data. We see that MOD outperforms GMF with respect to the three K values. This suggests that modularity-based circles can be a good choice to be integrated in the tool design.

[3]The algorithm is run on a computer with i7-2600 (3.4GHz, 8MB cache) CPU and 16GB memory. The source code and the datasets can be found at the author's website: http://i.stanford.edu/~julian/.

[4]The edge density in a circle should be larger than that on average in the whole graph.

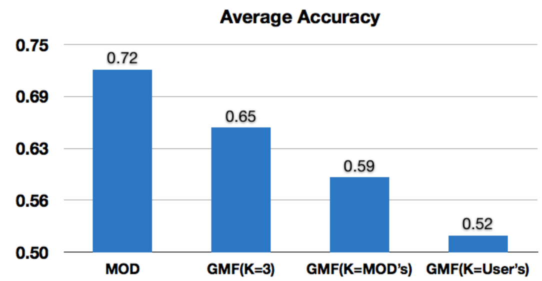

Fig. 1. Average accuracy scores of MOD and GMF on the ten Facebook users' data. The number of circles K for GMF is set to different values. They are K = 3, K is equal to that of MOD for each user and K is equal to that of each user's manual circles.

C. Discrepancy between Predicted and Manual Circles

Though a community discovery algorithm can predict reasonably good circles, it is unlikely that it can make a perfect prediction. This attributes to the fact that circle-creation is inherently subjective. In a labeling exercise [12], the manual circles were obtained by letting the users assign label(s) to describe their friends. The friends with the same label(s) are considered to be in the same circle(s). This encourages overlapping circles because users tend to assign multiple labels to a friend. In a card-sorting exercise [16], each friend's name is written on a card. Several cards were pre-selected and spread on a table. A participant is then asked to assign the rest of the cards to the pre-selected ones to form groups. In principle, the same friend can be assigned to different groups, but since people tend to assign a friend just once, overlaps are rare. We see that people create circles differently under different circumstances. Therefore, it is critical to enable the user to explore his friends based on an initial set of predicted circles that is "good enough", and adapt the circles for certain purpose. We may then evaluate the usefulness or effectiveness of these circles according to how well they have fulfilled that purpose. Exploration and adaptation of the circles by the user require an exploratory visualization approach.

D. Presentation and User Interaction of Circles

Major OSN sites such as Facebook, Google+ provide users with grouping functions. But except for Facebook smart lists, manual grouping has remained as the only way to organize and manage friends. It has also been quantitatively demonstrated that users' perceptions of their audience size do not match reality, since not enough feedback is provided for the users to be aware of the audience composition [17]. A visualization for EOSN circles was proposed [9]. It presents the composition of friends by labeling and resizing the circles. Our visualization addresses three improvements: 1) specifying the exact positioning of the circles to avoid overlapping layout; 2) specifying a way of browsing all the alters (members) in a circle. 3) enabling granular exploration of the circles. These points are particularly necessary given that the number of friends one might have in OSN is increasing, while empirical observations discourage displaying more than nine or ten items to be judged by a user [18], [19]. Moreover, current OSN lack the tools to let users manage the granular boundaries between multiple social groups as effectively as in their quotidian lives [20]. It thus becomes critical to provide users with a tool that enables granular exploration. This visualization design is detailed in the next section.

III. The Tool Design

A. Modularity-based Community Discovery with Granularity

The original MOD algorithm (Section II) is non-hierarchical. The communities are discovered when further division does not lead to an increase of the modularity. For each derived community, we obtain a subgraph. The same algorithm may then be applied to each subgraph, deriving sub-communities. As such, we adapt the original algorithm into a hierarchical one. We refer to this modified algorithm as H-MOD. In the next subsection, we show how circles or sub-circles are divided with user-interactions. When we adopt the community discovery algorithm hierarchically, we make the visualization more fine-grained.

B. Exploratory Visualization of Circles

In this subsection, we introduce a new form of visualization. The circles are aligned and manipulatable by zooming and dragging. Their sizes are scaled to provide a visual order. To encourage exploration, we only provide the user with "zooming/panning" and automatic division to explore the circles [21], [22]. We use desaturated, sometimes adjacent colors to make the visualization more aesthetic [22]. This also promotes the tool's usability [23]. The details of the design are as follows:

The ego's circles are presented as in Figure 2 (left). We call the area where the circles are drawn the canvas. The grey dot in the center of the canvas represents the ego. The radii and positions of the circles are determined according to the number of people in each circle[5]. The circularly aligned grey dots represent the members of that circle. The lighter grey dot in the center, which we call the handle of that circle, represents the circle as a whole, labeled with a name. With the handle, the user can move the whole circle around and address all the members to make visibility decisions (Section IV). The curves linking the members and the handle provides the user visual cues of the belongingness of the members. The members within the circles with small radii are hidden from sight in order to display a clean, non-overlapping overview. Hidden members and their names can be brought to display with zooming. When the user zooms into one circle, newly generated sub-circles are presented if the subgraph corresponding to the circle is divisible. This is depicted in Figure 3. The user can also align all the names in a (sub)circle in a grid on the canvas (Figure 4).

IV. Experimental User Study

In this section, we describe the experimental user study that evaluates the effectiveness of the exploratory visualization tool for users' *Visibility Decisions*, with Facebook smart lists as our baseline[6]. Facebook smart lists detect communities based on the information about the user's education, work and current city. For example, the friends who went to the same school as the user are put into the same list.

There were 16 participants, 25-45 years old, from eight countries. Among them are Ph.D researchers, company employees and Master students. We divided the the participants

[5]For the detailed circle-positioning algorithm, see http://people.cs.kuleuven.be/~bo.gao/papers/ASONAM2013/GranularCircles_position_algo.pdf.

[6]https://www.facebook.com/help/204604196335128/

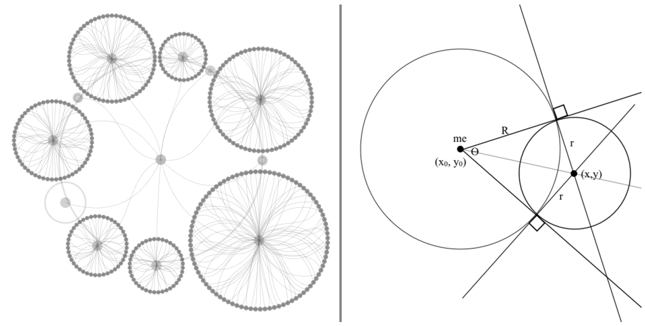

Fig. 2. Left: an overview of the circles' layout. Right: an illustration of drawing a circle around the ego.

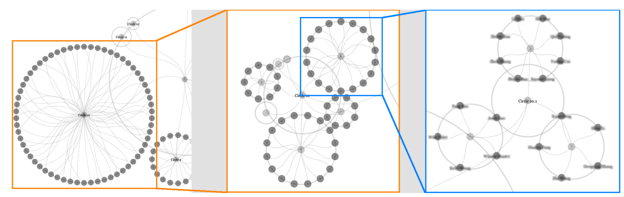

Fig. 3. An illustration of the hierarchical circles driven by a user's zooming. The names of the alters are blurred in this example to protect the user's privacy.

equally into two groups A and B. Group A used the tool we described in Section III. We took Group B as our baseline group. This group used the same visualization interface (Subsection III-B), but the underlying predicted circles were based on Facebook smart lists. The alters that were not in any smart list were put together into an extra circle. In this way, we removed the potential interference from using different interfaces. Our hypothesis is that users can make visibility decisions more effectively with the proposed exploratory visualization approach than the baseline approach. Each participant in both groups performed the following task comprised of two parts: elicitation of regrets in posts and visibility decision making.

Task: For the first part of the task, each participant was asked to identify his regretted posts. Though recent studies have investigated regrets in OSN from different aspects [24], [25], we chose to let our participants explicate their own regrets, because it is easier for a person to relate to his personal experience. A distinction was made between complete and partial regrets. A complete regret meant that the post was supposed to be seen by no one. A partial regret was where the participant did not mind his post being seen or intends his posts to be seen by some of the friends, but he failed to block the undesired friends. Since a complete regret entailed concealing the corresponding post completely, which would render a visibility decision trivial, we guided the participants to only think of partial regrets. Each participant was encouraged to think of three posts. A post needs to be specific enough to let the participant define its visibility to each friend. In total, 48 posts were collected. The types and the frequencies of the regretted posts are summarized in Table I. Note that some posts are of multiple types.

For the second part of the task, the participants were divided equally into two groups A and B. Each group has 8 participants and 24 posts. As shown in Figure 4, when a participant thinks an alter can see the post, he clicks on the dot, whose color turns from grey to blue. Clicking on the handle

TABLE I. PARTICIPANTS' REGRETTED POSTS

	Categories of Regretted Posts	Frequencies
a	I shouldn't express my bad mood or negative opinion.	6
b	I shouldn't ask for that advice or help.	1
c	There are uploaded photos depicting me in a way that I do not want to show to everyone.	15
d	language-specific posts	2
e	religious or political posts	5
f	I would have wanted to not show the post to that group of people for a particular reason.	6
g	I would have wanted to show the post only to that group of people for a particular reason.	6
h	inappropriate jokes	9

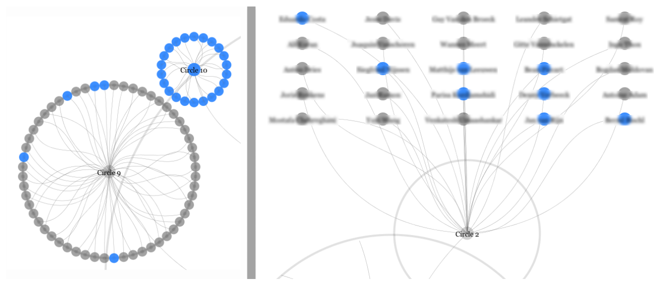

Fig. 4. By mouse-click, the participant can toggle individual members or a whole circle to indicate whether a post can be visible to them. An alter turns blue if the post is visible to him. Clicking the "handle" in the center of a circle toggles the whole circle (and its decedent circles if its hierarchical). On the right, we see that the members (labeled with their names) in a circle are aligned in a grid layout.

(the centered dot) of a circle makes the post visible to every member in that circle. The participants were allowed to work at their own pace until they are satisfied with their decisions.

Result: We use two measures to evaluate how effective the two approaches are for making visibility decisions: Accordance $Accordance(p) \in [0, 1]$ (Equation 3) that calculates the average percentage of the members in a circle who can/cannot see the post p, and Entropy $Entropy(p) \in [0, 1]$ (Equation 4) that calculates the overall information (in bits) needed to determine the whether a member in a circle can see a post. $Accordance(p) = 0$ or $Entropy(p) = 1$ means that on average, half a circle can see the post while the other half cannot, which means the set of circles is unhelpful. $Accordance(p) = 1$ or $Entropy(p) = 0$ means that on average, the members in the same circle have the same visibility status. That is, every circle, as a whole, can or cannot see the post, which is the case where the circles are fully utilized to make visibility decisions. The difference between the two measures is that the circles are treated equally in Accordance, while in Entropy, each circle is weighted according to the number of people in it, so that the visibility percentages in larger circles contribute more to the result.

The exploratory visualization interface is analogous to a binary-classification tree that tries to help the user utilize "pure" (sub)circles in terms of visibility decisions. The circles were firstly divided until they are indivisible according to the graph modularity or they are pure. We then used the leaves of the tree as the final set of circles [7]. Moreover, when there was only a small number of alters who could(not) see a post (e.g. less than five), Group A and B performed similarly well. This is because a participant can simply handpick the people that he wants to target, any grouping solution becomes trivial. Let us denote the number of alters to whom a post is or is not visible, whichever smaller, as α. We call a visibility decision with $\alpha \geq \alpha_{th}$ an α_{th}-*Visibility Decision*. Thereby, grouping tools can be of more service to a user when α_{th} is larger. When we raise α_{th} to five, 38 posts out of 48 remain in the two groups, with 19 posts for each group. Figure 5 shows the Accordance and Entropy scores on average for Group A and B with $\alpha_{th} = 1$ and $\alpha_{th} = 5$ respectively.

$$Accordance(p) = 2 \cdot (A_{show}(p) + A_{hide}(p)) - 1 \text{ with}$$
$$A_{show}(p) = \left(\frac{\sum_{c \in C_v} N_{c,p}}{N}\right) \frac{\sum_{c \in C_v} \frac{N_{c,p}}{|c|}}{|C_v|} \text{ and} \tag{3}$$
$$A_{hide}(p) = \left(\frac{\sum_{c \in C_{nv}} (|c| - N_{c,p})}{N}\right) \frac{\sum_{c \in C_{nv}} \frac{|c| - N_{c,p}}{|c|}}{|C_{nv}|}$$

$$Entropy(p) = \sum_{c \in C} \frac{|c|}{N} Entropy(c, p) \text{ with}$$
$$Entropy(c, p) = -\frac{N_{c,p}}{|c|} \cdot log_2 \frac{N_{c,p}}{|c|} \tag{4}$$
$$- \frac{|c| - N_{c,p}}{|c|} \cdot log_2 \frac{|c| - N_{c,p}}{|c|}$$

C_v is the set of the circles containing members to whom p is visible. C_{nv} is the set of the circles containing members to whom p is not visible. Note that C_v and C_{nv} may overlap. $N_{c,p}$ is the number of the alters to whom p is visible in the circle c. N is the total number of alters (including duplicates if circles overlap) in all the circles.

We see that Group A achieves higher accordance and lower entropy than Group B. This suggests that the fine-grained circles in our exploratory visualization design are taken more holistically into consideration than Facebook smart lists by the participants to make visibility decisions. The larger difference in Entropy than in Accordance between the two groups is attributed to the fact that the participants perform particularly better with the large circles in Group A than in Group B. We also observe the performances decrease with increased α_{th} in both groups, which is understandable since the easy cases for visibility decisions are removed. Note that the performance of Group B decreases more than Group A. This indicates that the advantage of our visualization design is more prominent when the participants were making hard visibility decisions. The performance changes are summarized in Table II.

TABLE II. PERFORMANCE CHANGE WITH α_{th} RAISED FROM 1 TO 5.

	Group A	Group B
Decreased Accordance	0.054 (8.64%)	0.061 (12.22%)
Increased Entropy	0.024 (12.24%)	0.095 (20.61%)

V. CONCLUSIONS

A. Limitations and Future Work

Several limitations of the design were identified in the process of the experimental user study. First, some participants recommended to use photos instead of name labels of the alters. Second, the layout of the circles could be more compact

[7]The detailed division algorithm and an example can be found at http://people.cs.kuleuven.be/~bo.gao/papers/ASONAM2013/GranularCircles_division_algo.pdf

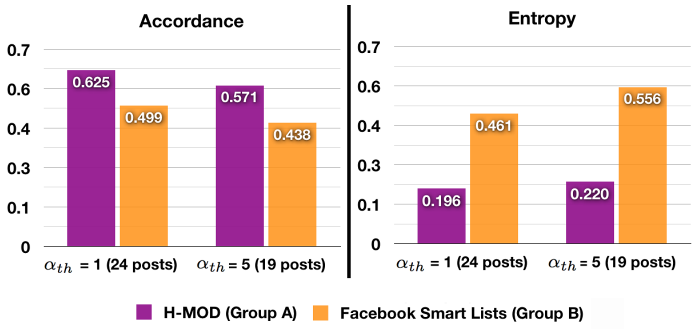

Fig. 5. Accordance and Entropy scores averaged over all posts in Group A and B, with $\alpha_{th} = 1$ and $\alpha_{th} = 5$. For a set of circles, the more it is in accord with the user's visibility decisions (Accordance) and the less bits of information needed to discern these decisions (Entropy), the better.

when the number of alters in a circle is small, so that the subcircles in its parent would not overlap with other parent circles. Third, the participants, especially in Group A, were curious about the way that the circles were formed, which suggests us providing extra means to present the unique characteristics of the circles, such as labeling, showing the links among the alters, etc. Another limitation of this work is due to the limited number of participants in the user study. A larger sample size is needed for deeper statistical analysis.

B. Summary

A privacy concern in OSN is that users may be unable to well manage their online information flows due to a large number of contacts. In this paper, we introduce an exploratory application that leverages community discovery algorithm and visualization to help users make more effective decisions on the visibilities of their online posts. We describe an experimental user study to evaluate how effective is this approach to users. The positive results of the user study show that our approach is indeed useful in its regard.

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